

A neutrosophic transfer learning approach for enhanced recyclable waste identification

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ABSTRACT

Recycling solid waste is crucial for achieving sustainable development, as it enhances economic efficiency while preserving environmental stability. However, many solid waste image modalities are susceptible to noise and uncertainty, which can compromise the performance of automated waste classification systems. Neutrosophic sets (NS) provide a robust framework for managing such uncertainty by decomposing images into three components: truth (T), indeterminacy (I), and falsity (F). Unlike traditional representations, the NS framework explicitly models ambiguity and vagueness inherent in visual waste data. This study investigates the effectiveness of deep learning (DL) models integrated with the NS framework for solid waste classification using the TrashNet dataset. The original images are transformed into the neutrosophic domain, enabling their representation through these three distinct components. Four DL architectures—DenseNet121, DenseNet169, InceptionV3, and MobileNetV2 are trained on images processed within the neutrosophic environment. The performance of these models is evaluated and compared across both the NS and fuzzy set (FS) domains using key metrics such as accuracy, precision, recall, and F1-score. The experimental outcomes demonstrate that the NS framework outperforms the FS approach, with the neutrosophic falsity component achieving a maximum accuracy of 97.64% using InceptionV3, highlighting its potential for more reliable waste classification in real-world applications. Overall, the proposed neutrosophic–deep learning framework offers a robust and scalable solution for intelligent solid waste management, supporting sustainable smart-city initiatives.

Keywords: Deep learning; Fuzzy set; Neutrosophic set; Sustainability; Waste classification.

1. INTRODUCTION

Waste generation is an unavoidable outcome of increasing population, rapid urbanization, and ongoing economic progress [1]. With economic growth and globalization, individuals are exposed to a broader range of goods and services, which contributes to a rise in waste production. As stated in the literature [2], solid waste consists of materials generated from various processes that are deemed no longer useful and are subsequently discarded. Many of these waste materials are recyclable [1, 2]. Nonetheless, the efficiency of recycling processes is contingent upon the precise categorization and systematic segregation of waste materials. While manual waste classification remains widely used, it is labor-intensive and susceptible to inaccuracies caused by human error. DL approaches, especially Convolutional Neural Networks (CNNs), support smart classification of solid waste by effectively mapping waste to designated categories.

CNNs are a form of DL model commonly applied to image classification problems. They are capable of identifying and extracting important visual features such as edges, patterns, and geometric shapes [3]. CNNs analyze images through a series of layered filters, enabling effective feature extraction and achieving high accuracy in classification tasks. In contrast to conventional machine learning methods like Support Vector Machine, CNNs can autonomously learn intricate patterns from raw data through artificial neural networks (ANNs), eliminating the need for handcrafted feature engineering [3, 4]. As a result, CNNs can capture features at varying levels of complexity, ranging from basic visual elements to advanced abstract representations. CNNs have demonstrated outstanding performance in numerous video and image analysis applications, such as self-driving vehicles, diagnostic imaging, and visual search systems. They exhibit strong potential in the domain of waste classification, fostering the advancement of streamlined and intelligent waste handling frameworks. Despite the need for substantial training data, DL models typically deliver strong performance during deployment [5].

In [6], the researchers introduced a DL-based method for waste classification utilizing a dataset that included several waste categories, including metal, plastic, and glass. In the literature [7], the EfficientNet model was used, through which an accuracy rate of 0.75 was achieved on the dataset. In another study [8], various DL architectures were trained and tested on the TrashNet dataset for automated waste classification. The researchers compared models including Inception, VGG, and ResNet, ultimately finding that the hybrid Inception-ResNet model achieved the highest performance, recording an accuracy of 0.8806.

In [9], the researchers designed a five-layer CNN specifically for classifying waste images. To mitigate overfitting, they applied data augmentation strategies during training. The proposed model achieved an overall accuracy score of 0.8088. Likewise, the study presented in [10] introduced an innovative deep learning (DL) model for advanced waste management. To improve the precision and efficiency of waste categorization, the authors proposed a new learning method. It outperformed VGG16, AlexNet, and ResNet34, with an accuracy of 0.9453. In [11], a neural network-based approach was developed to categorize waste into non-recyclable, recyclable, and organic types. The model recorded accuracies of 83.77% during training and 81.25% during testing.

The theory of NS, developed by Florentin Smarandache in 1995 and further formalized in 1999 [12, 13], extends classical logic and FS theory to address indeterminacy and imprecision. While In [14, 15] FS theory refines classical logic by allowing truth values to range continuously within the interval $[0, 1]$, NS theory incorporates three distinct membership components—truth, indeterminacy, and falsity—that offer a more comprehensive structure for representing uncertainty. NS theory has found applications in multiple areas of computer science, such as pattern recognition, data preprocessing, medical diagnostics, and sustainability [16–18].

FS and NS have been integrated with DL techniques for medical imaging tasks. In [19], fuzzy edge detection combined with DL achieved 81% accuracy for early COVID-19 detection. NS was shown to enhance performance on limited COVID-19 X-ray data by decomposing images into truth, indeterminacy, and falsity components [20]. Similarly, [21] introduced a Neutrosophic Multiple Deep CNN with a similarity score, effectively classifying skin cancer images as benign or malignant.

A recent study [22] proposed an Optimized Neutrosophic Deep Learning (ONDL) model that integrates AlexNet, neutrosophic conversion, and Grey Wolf Optimization. The model was tested on two publicly available datasets, DSWM1 and DSWM2, and achieved impressive classification accuracies of 91.89% and 85.32%, respectively.

Studies [23, 24] have applied deep learning and IoT-based systems for intelligent waste classification and management, achieving high accuracy in identifying different waste types and optimizing collection processes. Furthermore, recent literature [25–28] demonstrates that various types of waste including construction and electronic waste, plastics, and stone residues can be effectively repurposed in building materials, enhancing mechanical performance and durability while promoting sustainability and reducing environmental impact. This study explores the application of multiple DL models within the NS framework for classifying solid waste using the TrashNet dataset. The assessment focuses on six waste categories: paper, glass, trash, metal, plastic, and cardboard.

The core highlights of this research are summarized below.

- i. The inherent uncertainty in waste images is addressed using the three membership components of the NS domain: truth, indeterminacy, and falsity.
- ii. The integration of NS transformation with DL models is explored using four architectures: DenseNet121, DenseNet169, InceptionV3, and MobileNetV2.
- iii. A comparative evaluation is carried out between models trained on NS-transformed images and FS-transformed images, using evaluation metrics.
- iv. Among the models tested, InceptionV3 under the NS domain achieved the highest classification accuracy, demonstrating the effectiveness of NS-based preprocessing in improving waste classification performance.

The subsequent sections of this paper are organized as follows: Section 2 presents a comprehensive overview of the dataset utilized and the DL methodologies adopted in this research. Section 3 elaborates on the experimental framework, analyzes the results, and offers an in-depth discussion on the performance of both the proposed and benchmark DL models for waste classification. The concluding remarks and key insights are provided in Section 4.

2. MATERIALS AND METHODS

In this research, images from the neutrosophic and fuzzy domains are used to a pre-trained DL model for waste classification. The resulting models are then analyzed, evaluated, and compared. To examine performance differences among models trained on neutrosophic and fuzzy domain images, the research process is structured into multiple sequential phases, as illustrated in Figure 1.

2.1. Dataset

Recognizing and classifying recyclable waste is essential for sustainable human and environmental advancement. Furthermore, maintaining the global ecosystem is essential for ensuring a habitable planet in the modern era. This work focuses on improving automated waste classification performance through the integration of NS with DL models.

The dataset used in this study is TrashNet [29, 30], a publicly available benchmark dataset specifically designed for image-based recyclable waste classification. It includes six categories of waste: paper, glass, trash, metal, plastic, and cardboard. The dataset comprises images of waste materials captured on a white surface. In this study, the dataset was accessed through Kaggle [31], and each image was scaled to a pixel size of 224×224 for input into the model.

A total of 2,527 images are included in this dataset, which comprises the following categories:

- 594 paper
- 501 glass
- 137 trash
- 410 metal
- 482 plastic
- 403 cardboard

work utilized 70% of the dataset for training, with 15% each designated for validation and testing [30].

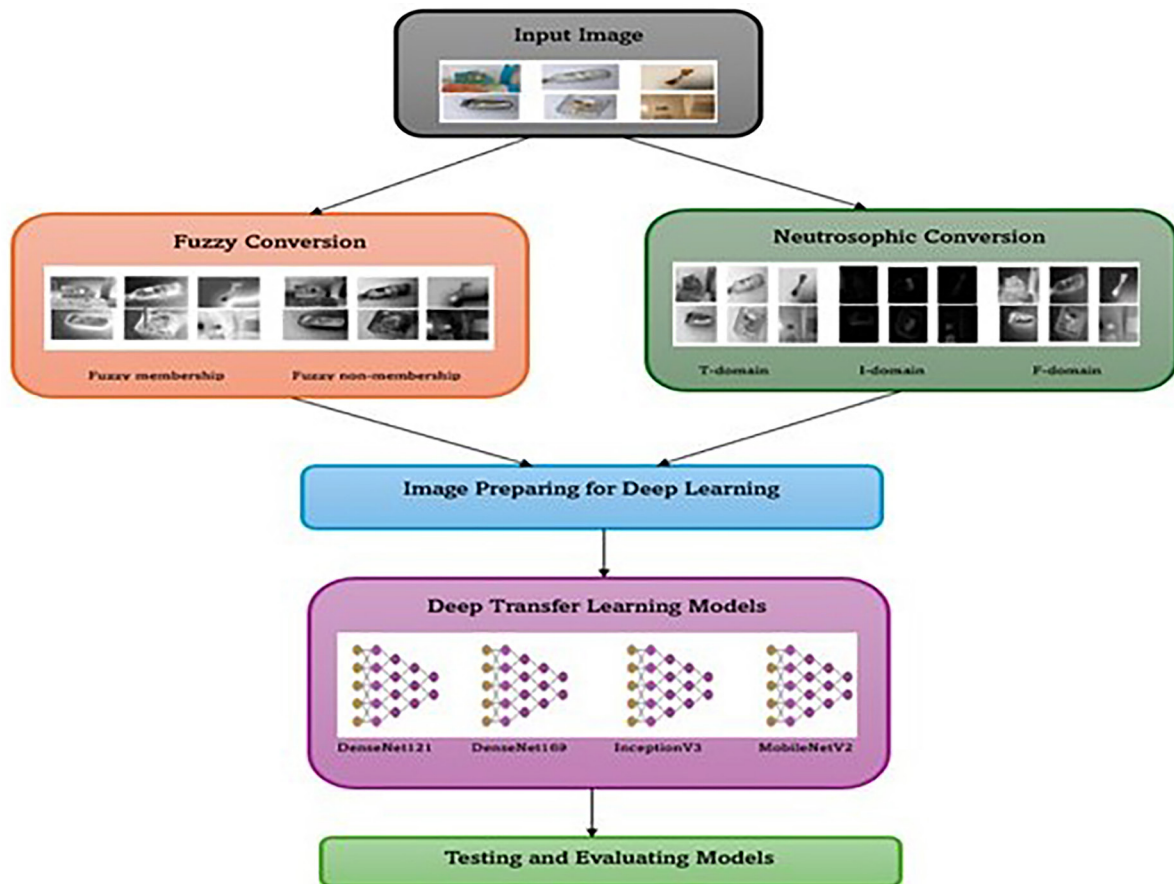


Figure 1: Research structured into multiple sequential phases.

2.2. Fuzzy set

FS is well-suited for handling uncertainty. It extends classical logic by allowing truth values to fall within the range of 0 to 1, rather than being strictly binary. Each element is assigned a membership degree, reflecting its level of association with the FS [14, 15]. This flexible representation makes fuzzy logic useful for image analysis, where pixel values often do not belong completely to one class but show partial association with multiple categories.

The process of converting images into FS form generally involves mapping pixel intensities to membership value and non-membership value that reflect how strongly each pixel relates to specific classes. This process is structured into three sequential stages:

- i. **Fuzzification:** This step involves mapping pixel intensity values to fuzzy sets, where membership values are used to assign a membership degree to each pixel based on category relevance. In this study, fuzzification helps convert raw image data into fuzzy domains so that uncertain or overlapping features (e.g., plastic and glass) can be better distinguished before applying deep learning models.
- ii. **Fuzzy inference:** Apply fuzzy logic to assign a membership degree to each pixel for every category. Logical rules or conditions can be used in this stage to adjust the pixel memberships, improving the representation of ambiguous regions in the image.
- iii. **Defuzzification:** The fuzzy outputs are converted into crisp values to finalize each pixel's category membership. This step produces a feature map that can be directly used by the deep learning classifier, linking fuzzy preprocessing with the learning stage.

This study employs a triangular membership function to determine the degree to which each pixel is associated with a FS during image conversion [32]. Its mathematical formulation is presented in Equations (1) and (2). The triangular membership function is chosen because of its simplicity and efficiency in mapping image intensities, providing smooth transitions between low, medium, and high membership values.

$$A = \{(x, \mu_A(y) \mid x \in U)\} \quad (1)$$

$$\mu(x; p, q, r) = \max(\min((x-p)/(q-p), (r-x)/(r-q)), 0) \quad (2)$$

Where $\mu_A(y)$ represents the membership value in the FS A , and the universe of discourse is denoted by U . The parameters p , q , and r represent the lower bound, the peak point, and the upper bound of the membership value, respectively. These parameters define how the pixel intensity is translated into a membership value. In this study, the values of p , q , and r are determined separately for each waste image category based on the intensity range of that category. Figure 2 illustrates the comparison of the input and FS domain images. Column (A) shows the original input image, (B) shows the fuzzy membership component that highlights regions strongly belonging to a class, and (C) shows the non-membership component, indicating uncertain or weak associations. This visual comparison demonstrates how fuzzy logic enhances feature separation before classification.

2.3. Neutrosophic set

NS extends both classical logic and FS. It is employed to handle ambiguous and uncertain scenarios. This framework was formulated by Florentin Smarandache [12, 13]. NS is characterized by three components:

- i. **Truth value (T):** Indicates how much an element belongs to the set.
- ii. **Indeterminacy value (I):** Measures the uncertainty or lack of information.
- iii. **Falsity value (F):** Represents how much the element does not belong to the set.

In neutrosophic image transformation, every pixel undergoes processing to extract its T, I, and F values, indicating its degree of truth, uncertainty, and falsity within the domain. Each image pixel, represented by $E(i, j)$, is associated with a set of neutrosophic values $E_{NS}(i, j) = \{T(i, j), I(i, j), F(i, j)\}$. The values of $T(i, j)$, $I(i, j)$, and $F(i, j)$ can be derived using the expressions outlined in Equations (3–6).

$$T(i, j) = \frac{\bar{f}(i, j) - f_{min}^{(c)}}{f_{max}^{(c)} - f_{min}^{(c)}} \quad (3)$$

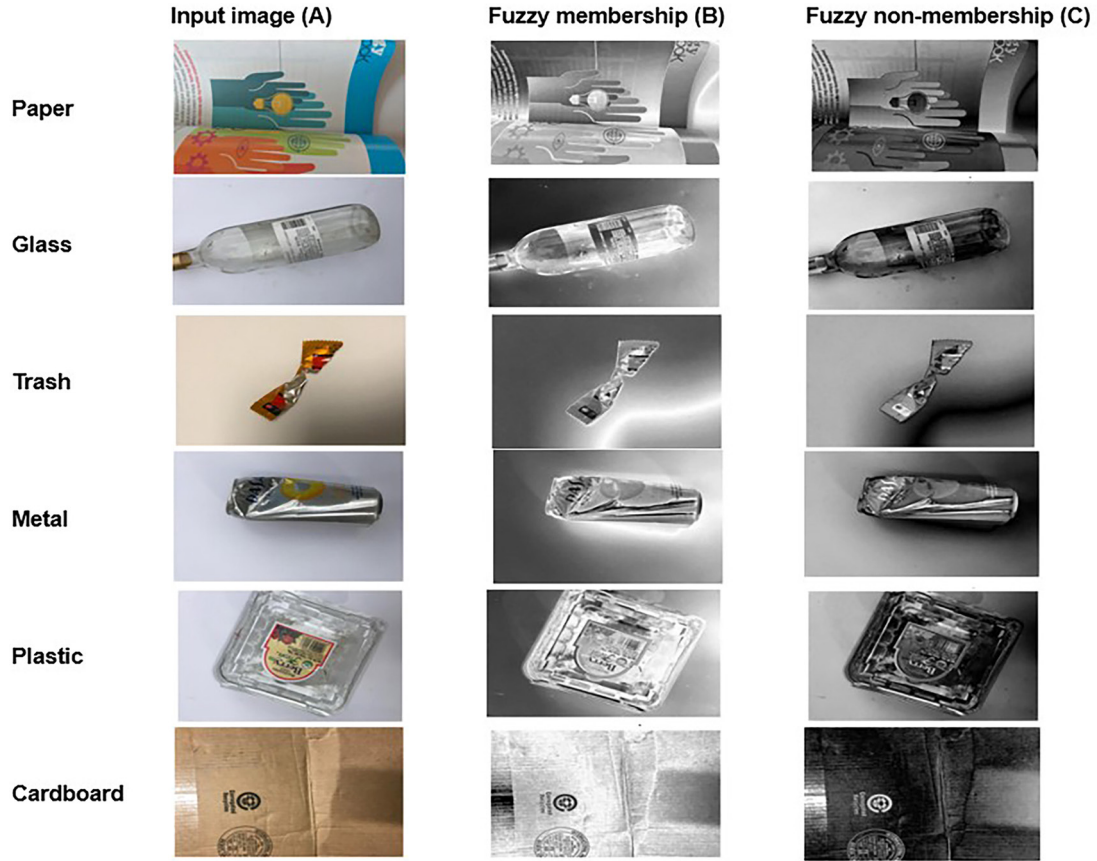


Figure 2: Visualization of FS conversion: (A) Input image, (B) Membership component, (C) Non-membership component.

$$I(i, j) = \frac{S(i, j) - S_{min}^{(c)}}{S_{max}^{(c)} - S_{min}^{(c)}} \quad (4)$$

$$S(i, j) = \text{abs}(f(i, j) - \bar{f}(i, j)) \quad (5)$$

$$F(i, j) = 1 - T(i, j) \quad (6)$$

Here, $f(i, j)$ denotes the grayscale intensity of the corresponding pixel, while $\bar{f}(i, j)$ refers to the local average gray value around the pixel at position (i, j) , and $S(i, j)$ represents the homogeneity value, defined as the absolute difference between the pixel intensity $f(i, j)$ and its corresponding local average $\bar{f}(i, j)$. The terms $f_{min}^{(c)}$ and $f_{max}^{(c)}$ are the minimum and maximum local mean intensities for the c^{th} image category. Similarly, $S_{min}^{(c)}$ and $S_{max}^{(c)}$ denote the minimum and maximum homogeneity values for the same category.

This category-wise normalization ensures that T, I, and F values are calculated relative to their own image group, improving the representation of each waste category in the neutrosophic domain. Once the image is transformed into the neutrosophic domain, the primary waste item is reflected under the T component, edge details and ambiguous areas are captured under the I component, while the background information is mostly retained under the F component. Figure 3 demonstrates the comparison between the input image and its respective representations within the NS domain.

2.4. Deep learning models

Transfer learning is a widely adopted DL technique where a model trained on a source task is repurposed as the foundation for a target task [33]. This pre-trained architecture was developed using a large-scale dataset and

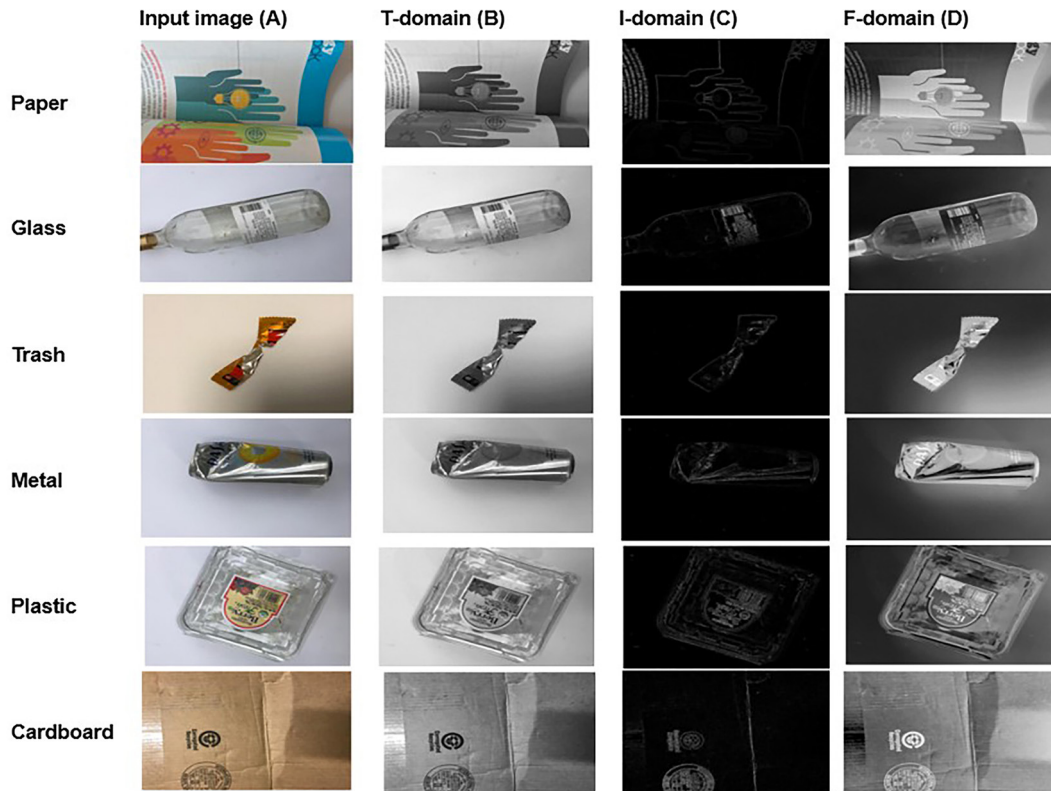


Figure 3: Visualization of NS conversion: (A) Input image, (B) T-domain, (C) I-domain, and (D) F-domain.

has acquired the ability to extract meaningful features from images. Therefore, applying transfer learning can enhance the performance of DL models and reduce training time.

This study employs four DL architectures, namely:

DenseNet121 [34].

DenseNet169 [35].

InceptionV3 [36, 37].

MobileNetV2 [38].

These models have been selected for their proven effectiveness in image classification tasks, including applications related to waste categorization, such as the TrashNet dataset. All selected models are based on the CNN, a robust architecture commonly employed for image-based classification and recognition tasks [39]. Convolutional layers apply a series of trainable filters, or kernels, to process input images and extract important features such as edges, patterns, and textures. CNNs have shown state-of-the-art performance across various computer vision applications.

3. RESULTS AND DISCUSSION

As described above, this study employs four widely used pre-trained DL models: DenseNet121, DenseNet169, InceptionV3, and MobileNetV2. Images processed using the NS and FS frameworks were used to train the models. The NS images were decomposed into T, I, and F components, while the FS images were converted into membership and non-membership representations. The models were trained using the Adam optimizer, configured with a 0.0001 learning rate, batches containing 16 images, and a maximum of 100 epochs, along with early stopping and learning rate reduction strategies to optimize performance and prevent overfitting.

3.1. Experiments setup

The experiments undertaken throughout this research were implemented on Google Colaboratory using Python 3.11.13, TensorFlow 2.18.0, and Keras 3.8.0, with GPU acceleration provided by an NVIDIA Tesla T4 (15.36 GB VRAM) and CUDA version 12.4.

3.2. Evaluation metrics

The proposed DL model is assessed using evaluation metrics as outlined in Equations (7) to (10).

- Accuracy – Represents the percentage of correctly predicted instances across all classes.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad (7)$$

- Precision – Refers to the proportion of correctly predicted positive instances out of all instances predicted as positive for a particular class.

$$Precision = \frac{TP}{(TP + FP)} \quad (8)$$

- Recall – The proportion of actual instances of a class that were correctly identified by the model.

$$Recall = \frac{TP}{(TP + FN)} \quad (9)$$

- F1 Score – Indicates the balanced average of precision and recall, calculated using their harmonic mean to provide a single measure of a model's accuracy.

$$F1\ Score = 2 \times \frac{recall \times precision}{recall + precision} \quad (10)$$

3.3. Experimental results

This section provides a comprehensive evaluation of the DL models applied to the processed image dataset, accompanied by a comparative analysis across multiple performance metrics. Tables 1 and 2 present the performance of the models on FS images, whereas Tables 3, 4, and 5 demonstrate the models' effectiveness on images converted to the NS domain.

Table 1: Performance of DL models on images with fuzzy membership values.

MODEL	ACCURACY %	PRECISION %	RECALL %	F1 SCORE %
DenseNet121	92.91	94.18	92.91	93.19
DenseNet169	95.01	95.58	95.01	95.11
InceptionV3	96.59	96.73	96.59	96.60
MobileNetV2	91.34	92.20	91.34	91.55

Table 2: Performance of DL models on images with fuzzy non-membership values.

MODEL	ACCURACY %	PRECISION %	RECALL %	F1 SCORE %
DenseNet121	90.03	91.90	90.03	90.55
DenseNet169	93.18	94.78	93.18	93.55
InceptionV3	97.38	97.41	97.38	97.37
MobileNetV2	94.49	95.36	94.49	94.65

Table 3: Performance of DL models on images with neutrosophic truth values.

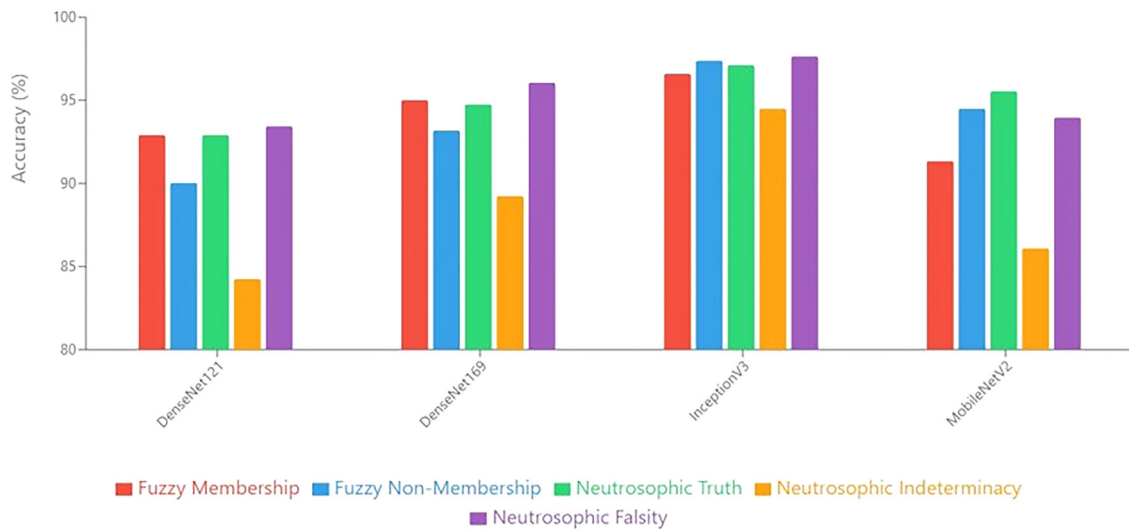
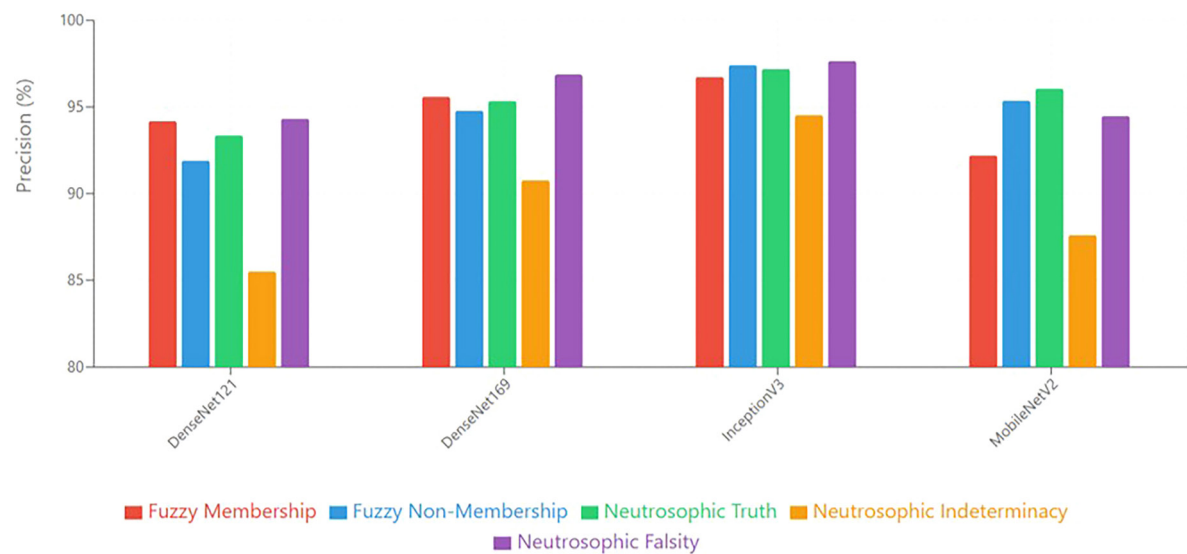
MODEL	ACCURACY %	PRECISION %	RECALL %	F1 SCORE %
DenseNet121	92.91	93.35	92.91	93.01
DenseNet169	94.75	95.34	94.75	94.84
InceptionV3	97.11	97.19	97.11	97.11
MobileNetV2	95.54	96.05	95.54	95.67

Table 4: Performance of DL models on images with neutrosophic indeterminacy values.

MODEL	ACCURACY %	PRECISION %	RECALL %	F1 SCORE %
DenseNet121	84.25	85.50	84.25	84.45
DenseNet169	89.24	90.76	89.24	89.64
InceptionV3	94.49	94.52	94.49	94.49
MobileNetV2	86.09	87.60	86.09	86.44

Table 5: Performance of DL models on images with neutrosophic falsity values.

MODEL	ACCURACY %	PRECISION %	RECALL %	F1 SCORE %
DenseNet121	93.44	94.32	93.44	93.65
DenseNet169	96.06	96.89	96.06	96.25
InceptionV3	97.64	97.65	97.64	97.63
MobileNetV2	93.96	94.47	93.96	94.02

**Figure 4:** Accuracy comparison of DL models.**Figure 5:** Precision comparison of DL models.

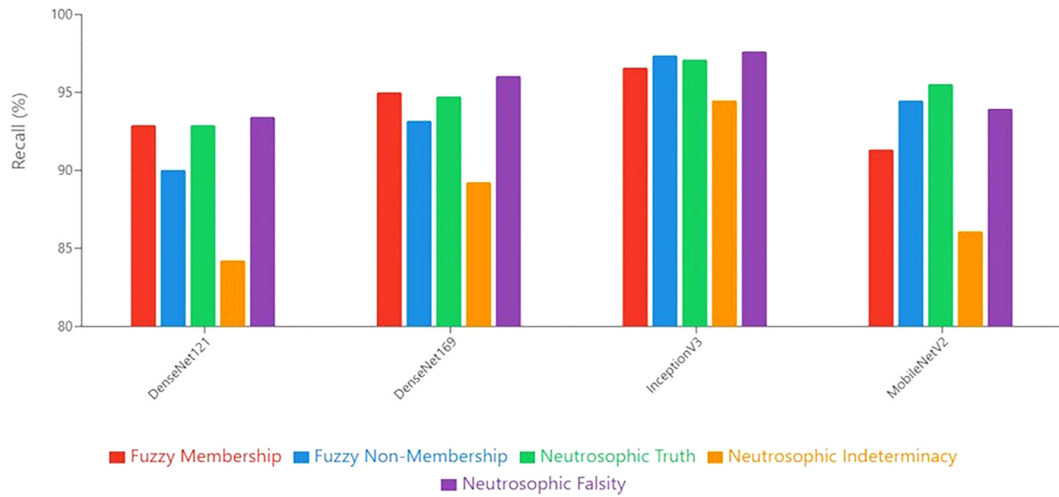


Figure 6: Recall comparison of DL models.

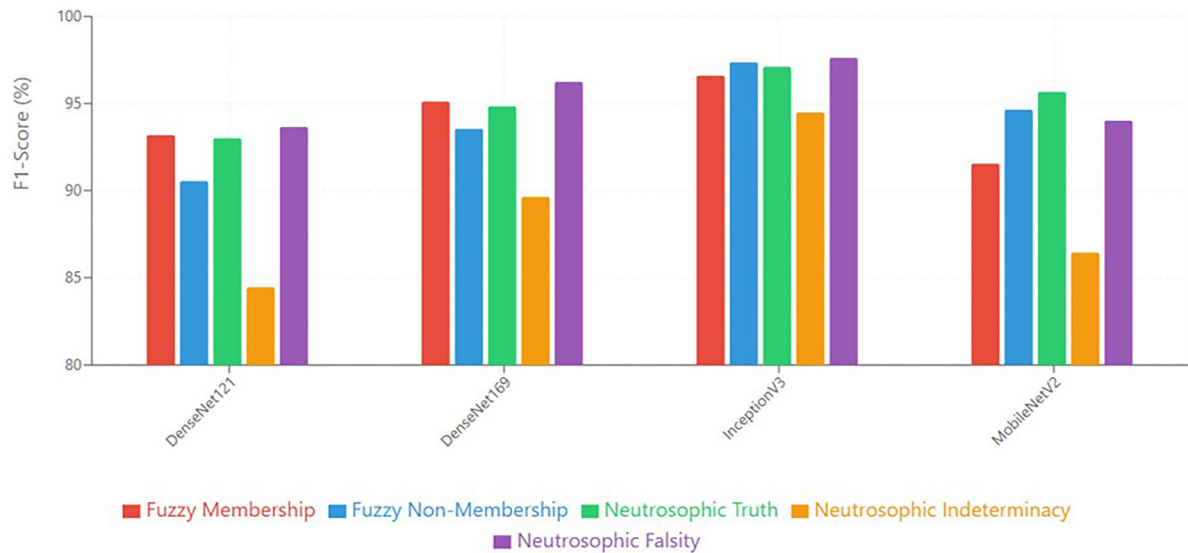


Figure 7: F1-score comparison of deep learning models.

The experimental findings demonstrated that, when comparing images processed in the NS domain with those in the FS domain, the NS-based images consistently yielded superior performance, highlighting the effectiveness of the NS framework in capturing discriminative features for classification. These improvements are further reflected in the graphical representations, where NS-based models exhibit consistently higher metric values across all evaluations. Among the NS components the falsity (F) domain achieved the highest accuracy across all experimental evaluations, demonstrating its strength in enhancing deep feature representation. Among the evaluated transfer learning architectures, InceptionV3 consistently delivered the best performance across all image categories. Notably, the highest model accuracy for a specific image type is reported in Table 5, where InceptionV3 attained 97.64% accuracy, 97.65% precision, and 97.64% recall on NS falsity-based images. The consistent upward trends of InceptionV3 observed in the figures visually confirm its robustness and stability compared with other DL models. Furthermore, Figures 4, 5, 6, and 7 provide a visual comparison of DL model performance across various evaluation metrics, further validating the effectiveness of the neutrosophic approach in improving waste classification. Unlike the tables that present numerical outcomes, these figures emphasize inter-model variations, illustrate the relative dominance of NS-based images, and visually confirm the consistent superiority of the proposed approach.

4. CONCLUSION

This research introduces a robust approach to solid waste classification by combining NS theory with DL models. Four pre-trained DL models were employed to evaluate the impact of NS transformations on classification

performance using the TrashNet dataset. Experimental findings demonstrated that the NS-based method consistently outperformed FS-based models across all architectures, particularly in various evaluation metrics. Among them, InceptionV3 achieved the highest performance, with 97.64% accuracy on images processed with NS falsity values, highlighting the superiority of DL over conventional machine learning techniques for this task. These results confirm that NS provides a solid framework for managing uncertainty and ambiguity in waste image data, resulting in improved model generalization and more accurate classification outcomes. However, the study is limited by its reliance on a single dataset and the absence of testing in real-time deployment scenarios. Future research will focus on expanding the dataset to include a broader range of real-world waste conditions, optimizing DL models for efficient deployment on edge computing devices, and exploring hybrid NS transformations alongside ensemble learning techniques to further enhance classification accuracy and scalability within smart city waste management systems.

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